Evaluating GPFARM Crop Growth, Soil Water, and Soil Nitrogen Components for Colorado Dryland Locations

J. C. Ascough II, G. S. McMaster, A. A. Andales, N. C. Hansen, L. A. Sherrod

Abstract. *Alternative agricultural management systems in the semi-arid Great Plains are receiving increasing attention. GPFARM is a farm/ranch decision support system (DSS) designed to assist in strategic management planning for land units from the field to the whole-farm level. This study evaluated the regional applicability and efficacy of GPFARM based on simulation model performance for dry mass grain yield, total soil profile water content, crop residue, and total soil profile residual NO_3-N across a range of dryland no-till experimental sites in eastern Colorado. Field data were collected from 1987 through 1999 from an on-going, long-term experiment at three locations in eastern Colorado along a gradient of low (Sterling), medium (Stratton), and high (Walsh) potential evapotranspiration. Simulated crop alternatives were winter wheat (*Triticum aestivum *L.), corn (*Zea mays *L.), sorghum (*Sorghum bicolor *L.), proso millet (*Panicum miliaceum *L.), and fallow. Relative error (RE) of simulated mean, root mean square error (RMSE), and index of agreement (d) model evaluation statistics were calculated to compare modeled results to measured data. A one-way, fixed-effect ANOVA was also performed to determine differences among experimental locations. GPFARM simulated versus observed REs ranged from -3% to 35% for crop yield, 6% to 8% for total soil profile water content, -4% to 32% for crop residue, and -7% to -25% for total soil profile residual NO_3-N. For trend analysis (magnitudes and location differences), GPFARM simulations generally agreed with observed trends and showed that the model was able to simulate location differences for the majority of model output responses. GPFARM appears to be adequate for use in strategic planning of alternative cropping systems across eastern Colorado dryland locations; however, further improvements in the crop growth and environmental components of the simulation model (including improved parameterization) would improve its applicability for short-term tactical planning scenarios.*

Keywords. *Agroecosytem, Crop residue, Crop yield, GPFARM, Model evaluation, Soil nitrogen, Soil water.*

Agricultural software developers are delivering increasingly comprehensive and sophisticated products (e.g., decision support systems (DSSs); simulation models; and budgeting, record keeping, irrigation, and fertilizer management tools) for use by farmers and ranchers. In the Great Plains, there has been a recognized need for a systems approach in agricultural research and development to attain economic and environmental sustainability (Ascough et al., 2002). Likewise, there has been a recognized need for system-level decision support tools for agricultural advisors and producers. Despite interest by agricultural advisors and producers, most agricultural software is rarely adopted or used on the farm or ranch, especially DDSs and simulation models (Ascough et al., 1999, 2002). Furthermore, scientists and researchers developing these decision support tools are typically reluctant to release them for use until they are reasonably confident that the software output and results are sufficiently accurate to meet design objectives.

The USDA-ARS Agricultural Systems Research Unit (ASRU) has developed a decision support system named GPFARM (Great Plains Framework for Agricultural Resource Management). GPFARM 2.6 encompasses stand-alone components such as a user interface, simulation model, and databases (Ascough et al., 2002; McMaster et al., 2002; Shaffer et al., 2000) that, when used in conjunction with other components (e.g., farm economic budgeting and multicriteria decision analysis modules), provide a unique decision support tool for farmers and ranchers. The general purpose of GPFARM is to serve as a whole-farm/ranch DSS for strategic planning across the Great Plains by considering production, economic, and environmental impact analysis, thereby allowing assessment and comparison of alternative agricultural management systems. Agricultural consultants, farmers, and ranchers are targeted as the primary users of GPFARM. The major design requirements, based on intended practical application, were that the system: (1) be simple to understand and easy to use, (2) have minimum input data and parameter requirements, and (3) produce scientifically sound and defensible results.

GPFARM has been evaluated in several different ways, including general farm/ranch testing with producers (i.e., expert opinion evaluation), experimental field plot or scientific testing, and trend analysis. For example, McMaster

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et al. (2003) used three winter wheat plant parameter sets with different calibration levels to evaluate the GPFARM 2.01 crop growth module. Andales et al. (2003) evaluated GPFARM 2.01 crop growth, water balance, and nutrient cycling modules using rotation-specific summit landscape position data from three eastern Colorado locations. Additional evaluation of GPFARM is occurring through two ongoing cooperative research agreements: (1) GPFARM has been adopted by the Colorado Association of Wheat Growers and distributed to over 600 members for general on-farm use, and (2) Decision Commerce Group, Inc. (Billings, Montana) is currently evaluating various model components for wider technology transfer.

As indicated above, different GPFARM simulation modules have been independently tested to varying degrees. However, further evaluation is needed at a whole-system level to quantify crop yield and water quality model output response, especially for strategic planning under the environmental conditions in the immediate target area of eastern Colorado. In addition, many corrections and enhancements have continued to be made to the GPFARM 2.6 modules. Therefore, the main objective of this study was to evaluate the long-term (i.e., multi-year) performance of GPFARM 2.6 in simulating grain yield, soil water, crop residue, and soil NO_3-N across a north-to-south potential evapotranspiration (PET) gradient in eastern Colorado dryland cropping systems. A secondary objective was to examine the efficacy of different statistical techniques commonly used in assessment and evaluation of simulation model performance.

Materials and Methods

GPFARM Simulation Model

The GPFARM DSS is a conglomerate of major components designed to serve as an extensive decision support tool for farmers and ranchers (fig. 1). These components include: (1) a Microsoft Windows-based graphical user interface (GUI); (2) Microsoft Access databases containing soil, crop, weed, climate, chemical, and economic parameters needed in the simulations and analysis of results; (3) an object-oriented modeling framework (Shaffer et al., 2000) that integrates modules for simulating soil water dynamics, N dynamics, crop growth, weed growth, beef cattle production, pesticide transport, and water/wind erosion; (4) a set of management scenario analysis tools (e.g., a multi-criteria decision making model (MCDM), graphical/spatial output visualization/ summary report tables, and a stand-alone farm/ranch economic analysis); and (5) an internet-based GPFARM information system (http://infosys. ars.usda.gov) containing numerous links to information on various farm and ranch management options. Simulation modules that are directly related to the model output responses presented in this article are briefly described below.

Crop growth module. This module is based on the Water Erosion Prediction Project (WEPP) model crop growth component (Arnold et al., 1995; Deer-Ascough et al., 1998), which was originally derived from the EPIC crop growth model (Williams et al., 1989). It has been further modified in GPFARM to incorporate elements from the Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC) model (Kiniry et al., 1992). The crop growth component can be characterized as using an energy- or carbon-driven approach, whereby potential daily biomass accumulation is based on an energy to biomass conversion factor and the interception of light by the canopy (as represented by the LAI and light extinction coefficients). Stress factors for water and nitrogen are computed using inputs from other independent modules within GPFARM. Carbon and N are partitioned to plant components (e.g., leaves, roots, and grain). Currently, GPFARM is parameterized for winter wheat (*Triticum aestivum* L.), corn (*Zea mays* L.), proso millet (*Panicum miliaceum* L.), sunflower (*Helianthus annuus* L.), sorghum (*Sorghum bicolor* L.), and foxtail/hay millet (*Setaria italica* L., Beauv.).

Soil properties module. This module estimates the soil water retention curve (WRC) based on Brooks and Corey (1964) parameters calculated from basic soil property information (e.g., soil texture, bulk density, and organic matter content). This information is obtained from the GPFARM STATSGO soil survey database or provided directly by the user. The saturated hydraulic conductivity (K_{sat}) is obtained from effective porosity (Ahuja et al., 1989), and unsaturated hydraulic conductivity is estimated from the WRC and K_{sat} using the Campbell (1974) approach. The effects of tillage, residue cover, and reconsolidation (due to rainfall) on bulk density are estimated using the approach of Williams et al. (1984), and hydraulic properties are updated using the regression equations of Rawls and Brakensiek (1985).

PET module. This module is adapted from the Root Zone Water Quality Model (RZWQM; Ahuja et al., 2000) and calculates daily potential crop transpiration and soil evaporation using the extended Shuttleworth-Wallace model (Farahani and Ahuja, 1996). Net radiation is calculated, and the available energy for potential transpiration, bare soil evaporation, and/or residue-covered soil evaporation is partitioned. Potential transpiration, soil evaporation, and residue evaporation values then serve as the upper limits of actual ET calculated in the water balance module.

Water balance module. This module is a simplification of the RZWQM water balance routines (Ahuja et al., 2000) for determining infiltration and soil water/chemical fluxes between and during precipitation (rainfall, irrigation, or snowmelt) events. The Green-Ampt (Green and Ampt, 1911) method, as executed in RZWQM, is used to simulate infiltration during a rainstorm at small time intervals. Redistribution of soil water is obtained by Darcian fluxes between adjacent soil horizons or sub-horizons, calculated at a 3 h to daily intervals. Both space and time steps are coarser as compared to RZWQM, which uses Richard's equation for soil water redistribution; however, the simpler scheme in GPFARM accurately maintains mass balance. Surface water supply exceeding the infiltration capacity in any time interval of precipitation becomes surface runoff. Drainage from the soil profile is estimated by assuming a unit gradient at the bottom layer.

C and N cycling module. This module is based on the Nitrogen Leaching and Economic Analysis Package (NLEAP) model (Shaffer et al., 1991, 2001) and simulates soil C and N cycling in surface residues and within the soil. Each soil organic matter pool—a fast, readily decomposable pool; a slower humus pool; and a surface residue pool (Shaffer et al., 2001)—has a unique C:N ratio and is subject to first-order decomposition. Processes of nitrification, ammonia volatilization, denitrification, crop N uptake, and nitrate-N leaching are also simulated.

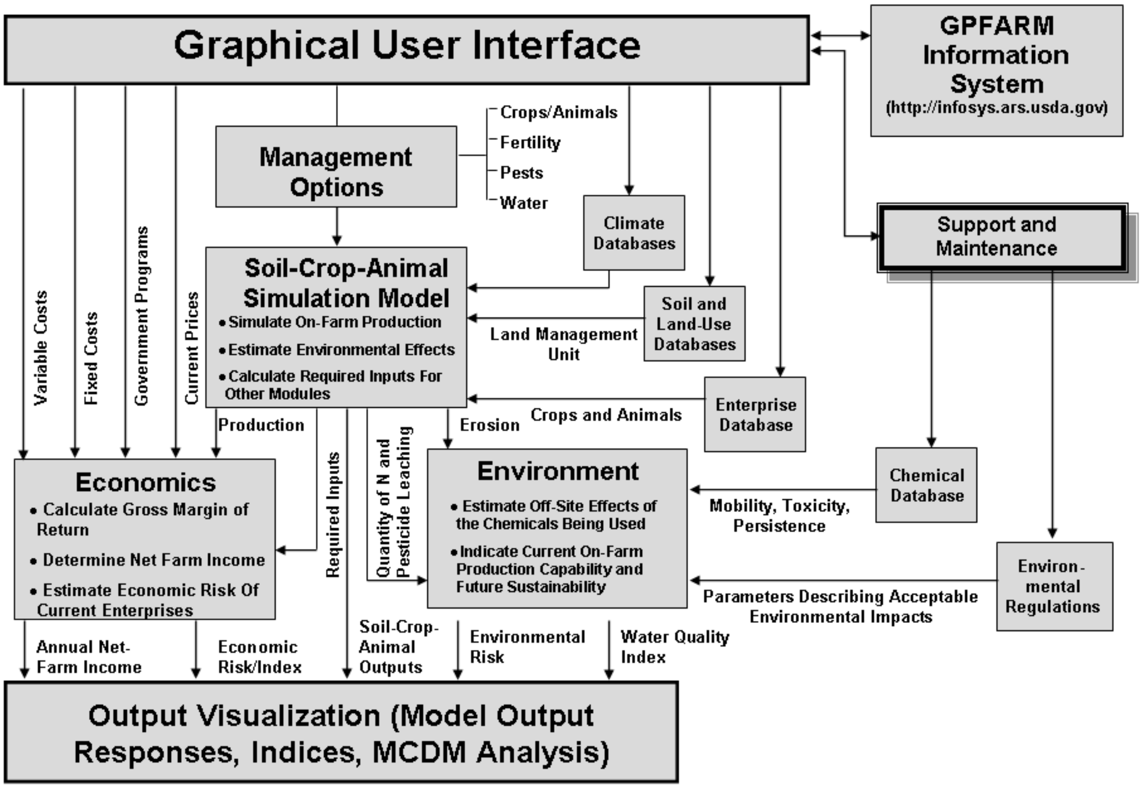

Figure 1. Schematic diagram of GPFARM DSS components. Arrows indicate the flow of information.

For a more comprehensive description of these modules and the GPFARM DSS, see Ascough et al. (2002), McMaster et al. (2002, 2003), and Shaffer et al. (2004).

Site Description and Cropping Systems

The long-term sustainable Dryland Agroecosystems Project (DAP) was initiated in 1985 at three sites in eastern Colorado (Sterling, Stratton, and Walsh) to evaluate the effects of cropping intensity on production, water use efficiency, and selected soil chemical and physical properties (Peterson et al., 1993). This experiment has three major variables: (1) PET gradient, (2) topography (slope position), and (3) cropping intensity under no-till management (fig. 2). Soils at each site were under conventional tillage crop-fallow management for at least 50 years prior to the initiation of this study in 1985.

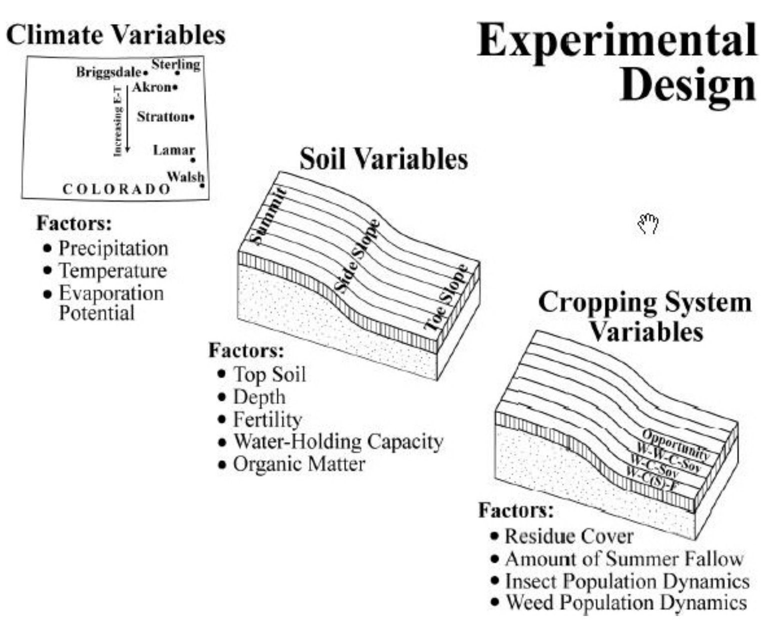

Figure 2. Schematic diagram of the Dryland Agroecosystems Project experimental design with climate, soil, and cropping system variables (from Peterson et al., 2000).

Table 1. Elevation, mean annual temperature, mean annual precipitation, and other climatic properties of the eastern Colorado experimental sites (adapted from Sherrod et al., 2005).

Experimental Site	Latitude and Longitude	Elevation (m)	Mean Annual Temp. (°C)	Mean Annual Precipitation (1961-1990) (mm)	Days Above 32°C (days)	Growing Season Open-Pan Evaporation (mm)	Deficit Water[a] (mm)	Relative Potential Evapotranspiration (PET)
Sterling	40° 22′12″ N, 103° 7′ 48″ W	1341	9.3	440	42	1600	−1160	Low
Stratton	39° 10′ 48″ N, 102° 15′ 36″ W	1335	10.8	415	54	1725	−1310	Medium
Walsh	37° 13′ 48″ N, 102° 10′ 12″ W	1134	12.2	395	64	1975	−1580	High

[a] Deficit water = precipitation − open-pan evaporation.

Table 2. Range of physical and hydraulic properties across soil horizons at the eastern Colorado experimental sites.

Landscape Position	Soil Profile Depth (cm)	Bulk Density (g cm^{-3})	Sand (%)	Clay (%)	Organic Matter (%)	Porosity[a] (m^3 m^{-3})	Water Content[a] 33 kPa (m^3 m^{-3})	Water Content[a] 1500 kPa (m^3 m^{-3})	K_{sat}[a],[b] (cm h^{-1})
Sterling									
Summit	141	1.21-1.43	24.5-45.1	20.7-38.1	0.13-1.37	0.46-0.54	0.24-0.34	0.14-0.20	0.86-3.67
Sideslope	150	1.18-1.61	26.9-85.7	2.2-31.3	0.05-1.50	0.39-0.55	0.11-0.32	0.05-0.18	2.14-16.18
Toeslope	159	1.30-1.54	30.3-76.0	9.5-27.2	0.10-2.30	0.42-0.51	0.14-0.30	0.08-0.17	1.01-6.53
Stratton									
Summit	150	1.31-1.41	20.0-35.0	14.0-36.0	0.01-1.76	0.47-0.51	0.24-0.35	0.11-0.21	0.23-3.95
Sideslope	150	1.32-1.64	21.3-72.4	16.1-34.9	0.03-1.76	0.38-0.50	0.19-0.35	0.11-0.20	0.34-3.60
Toeslope	152	1.22-1.41	23.0-42.0	18.0-36.0	0.86-1.78	0.47-0.54	0.24-0.35	0.12-0.21	0.31-4.29
Walsh									
Summit	155	1.17-1.49	6.5-67.6	14.3-39.9	0.26-1.02	0.44-0.56	0.18-0.39	0.11-0.22	0.49-5.22
Sideslope	157	1.19-1.55	7.0-71.5	10.4-38.4	0.48-0.79	0.42-0.54	0.15-0.38	0.08-0.22	0.11-5.52
Toeslope	171	1.32-1.51	23.1-70.0	17.0-31.8	0.19-1.76	0.43-0.50	0.18-0.33	0.11-0.19	0.33-4.21

[a] Estimated in GPFARM from Brooks-Corey parameters.
[b] K_{sat}, saturated hydraulic conductivity.

The three sites represent a gradient of increasing PET from north to south, but all have similar long-term mean annual precipitation (ranging from 395 to 440 mm; table 1). The deficit water (i.e., precipitation minus open-pan evaporation) also increased from north to south, with −1160, −1310, and −1580 mm year^{-1}, for Sterling, Stratton, and Walsh, respectively. At each site, a topographic variable is represented by summit, sideslope, and toeslope landscape positions along a catenary sequence. A range of physical and hydraulic properties across soil horizons for these landscape positions at the three DAP sites is given in table 2, along with the soil hydraulic properties estimated by GPFARM. Each slope position is correlated to a unique soil series common to the geographic area such that nine different soil series are represented across the three sites (Peterson, et al., 1993).

Various cropping systems, representing a gradient of cropping intensities, were placed in strips across catenary sequences at each site. The cropping systems were wheat-fallow [WF], wheat-corn (or sorghum for the Walsh site)-fallow [WC(S)F], and wheat-corn (or sorghum for the Walsh site)-millet-fallow [WC(S)MF]. Each crop was present in each cropping system every year. The cropping system gradient was as follows: WF had an intensity factor of 0.50 (cropped years divided by total years in the rotation), and the intensity factors for WC(S)F and WC(S)MF were 0.67 and 0.75, respectively. Crops were planted using no-till planters and drills that only disturbed the soil in a narrow band to allow for a seed row. Fertilizer N (32-0-0) and P (10-34-0) were applied based on annual soil tests for available N and P. Available soil N was obtained by KCl extraction with Cd reduction for nitrate, and available soil P was obtained by sodium bicarbonate extraction using the Olsen method (Olsen and Sommers, 1982). Grain yield response to P is not currently simulated in GPFARM, but it was found to be small to negligible in the experiment.

Measured Data

Measurements relevant to the evaluation of GPFARM 2.6 included daily weather data, grain yield, soil water content, crop residue dry mass, and soil residual NO_3−N. Additional variables were measured (e.g., final dry matter biomass), as described by Peterson et al. (2000), but were not considered in this study. An automated weather station at each site measured daily maximum and minimum air temperature, mean relative humidity, precipitation, total solar radiation, wind direction, and mean wind speed. Cumulative precipitation for the eastern Colorado experiment locations over the simulation period is shown in figure 3.

Grain yield was measured with a plot combine, while total aboveground biomass was measured at harvest by hand sampling. The harvest indices (grain yield/total biomass) were determined from the hand samples. Soil water content (30 cm increments down to a depth of 150 cm) was measured at strategic times (e.g., bi-weekly during summer months) in each cropping system by use of a neutron attenuation probe. Crop residue dry mass was measured at planting and immediately before harvest for each crop in each cropping system. Soil residual NO_3−N (at varying increments down to a depth of 150 cm) was measured prior to planting to determine fertilizer N requirements.

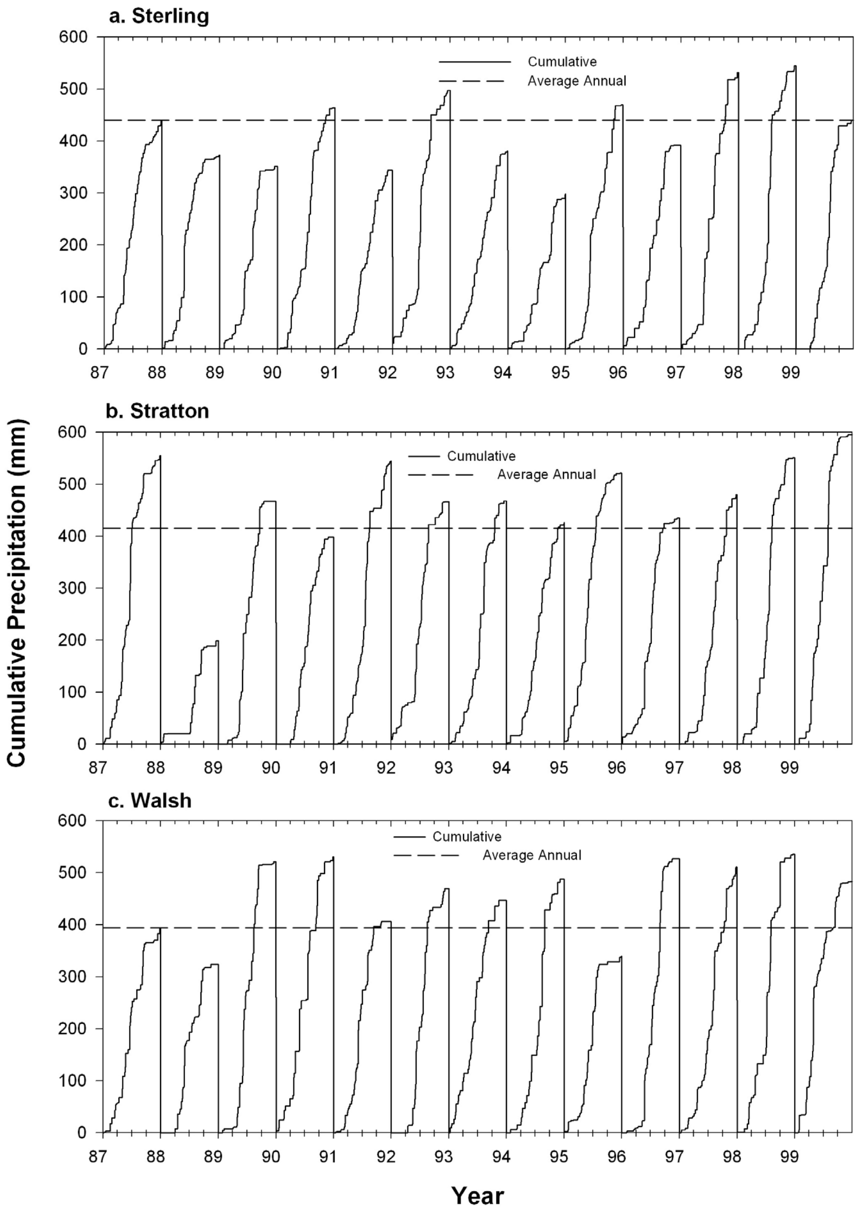

Figure 3. Cumulative precipitation (with annual average overlay) for the eastern Colorado experiment locations over the simulation period (1988-99).

GPFARM Model Initialization, Calibration, and Statistical Evaluation

GPFARM climate input data included observed daily precipitation, maximum and minimum air temperatures, solar radiation, wind speed, and relative humidity obtained from the on-site weather stations. The simulation model was initialized using observed data for soil profile water content, crop residue, and soil profile residual NO_3-N corresponding to simulation start dates. Observed bulk density, texture, and organic matter content of the soil layers (table 2) were also input into GPFARM. From these properties, the model estimated the soil water retention curve, soil porosity (or saturated water content), soil water content (WC) at field capacity [WC (33 kPa)], soil water content at wilting point [WC (1500 kPa)], and saturated/unsaturated hydraulic conductivity (Rawls and Brakensiek, 1985; Ahuja et al., 1989, 1999). Actual soil horizon depths and N application rates were used in the simulations (data not shown).

Model calibration was performed for only the maximum potential leaf area index (XMXLAI) and potential harvest index (HI) plant growth parameters. For other plant growth parameters of the crops involved in the study (i.e., winter wheat, corn, proso millet, and sorghum), best parameter estimates from the literature (e.g., McMaster et al., 2003) were used (table 3) and verified to be within the ranges recommended by Arnold et al. (1995) and Kiniry et al. (1995). No calibrations were performed for the soil water, soil residual NO_3-N, and crop residue decomposition processes. The XMXLAI for each crop was adjusted (within ranges expected for the study site) to minimize the root mean square error (RMSE) of simulated total aboveground biomass. The HI for each crop was adjusted by trial and error (based on observed HI) to minimize the RMSE of HI predictions. Toeslope landscape position data from the Sterling site (data not shown) were used to obtain calibrated values of XMXLAI and HI for winter wheat, corn, and proso millet. The XMXLAI and HI values for sorghum were

Table 3. Important crop parameter values used in the GPFARM simulations.[a]

Parameter	Definition	Units	Parameter Value: Winter Wheat	Corn	Proso Millet	Sorghum
GDDMAX	Growing degree-days from planting to maturity	°C days	2300	1500	1300	1800
HI[b]	Harvest index	0-1 ratio	0.48	0.65	0.45	0.50
HMAX	Maximum canopy height	m	0.91	2.60	1.20	1.01
XMXLAI[b]	Maximum potential leaf area index (LAI)	m^2 m^{-2}	2.00	3.50	2.40	3.50
BEINP	Biomass to energy conversion ratio for a crop	kg MJ^{-1}	30.00	35.00	35.00	25.00
BN1	Normal fraction of nitrogen in crop biomass at emergence	0-1 ratio	0.060	0.040	0.044	0.044
BN2	Normal fraction of nitrogen in crop biomass at mid-season	0-1 ratio	0.023	0.016	0.016	0.016
BN3	Normal fraction of nitrogen in crop biomass at maturity	0-1 ratio	0.013	0.013	0.013	0.013
BTEMP	Base temperature (air) used in calculating growing-degree days	°C	0.00	10.0	5.0	10.0
CRIT	Growing degree days from planting to emergence	°C days	140.0	60.0	65.0	60.0
DLAI	Fraction through growing season when LAI begins to decline	0-1 ratio	0.70	0.80	0.80	0.85
EXTNCT	Radiation extinction coefficient	unitless	0.65	0.65	0.65	0.60
OTEMP	Optimal temperature for plant growth	°C	20.0	25.0	20.0	27.5
RDMAX	Maximum rooting depth	m	1.5	1.5	1.0	1.5
RSR	Root biomass to shoot biomass ratio	0-1 ratio	0.25	0.25	0.25	0.25
SPRIOD	Period over which senescence occurs	days	14	30	30	40
RLAD	Rate of LAI decline	unitless	1.0	1.0	1.0	1.0
PPOP1	Plant density at FMLAI1	plants m^{-2}	125	4	125	5
FMLAI1	Fraction of XMXLAI corresponding to PPOP1	0-1 ratio	0.60	0.47	0.60	0.43
PPOP2	Plant density at FMLAI2	plants m^{-2}	250	7	250	15
FMLAI2	Fraction of XMXLAI corresponding to PPOP2	0-1 ratio	0.95	0.80	0.80	0.79

[a] Adapted from Andales et al. (2003).
[b] Calibrated to optimize predicted total biomass, HI, and grain yield.

calibrated using Walsh summit landscape position data (wheat-sorghum-fallow rotation beginning with the sorghum phase in 1988; data not shown) because sorghum was planted only at that location. The calibrated parameters were subsequently used for the other landscape positions at the experimental sites in this study (e.g., the Sterling toeslope calibrated parameters were used for all three Stratton landscape positions).

For the calibration at the Sterling toeslope and Walsh summit landscape positions, simulated grain yield agreed with observed values, and simulated total soil profile water content was slightly lower than observed (fig. 4). The calibrated HI values for winter wheat (HI = 0.48) and corn (HI = 0.65) (table 3) were considerably higher than those recommended by Kiniry et al. (1995), which were 0.40 and 0.55, respectively. Although the simulated harvest-time HI values, (which were adjusted in the model for water, temperature, and N stresses) ended up much lower, the high calibrated HI value for corn may have resulted in an overall bias towards overpredicting yield. Andales et al. (2003) provides additional discussion on the model calibration process.

The simulation periods for evaluation began in 1988 and ended in 1997, 1999, and 1993 for the WF, WC(S)F, and WC(S)MF rotations, respectively. Average (i.e., from two replicates) total soil profile water content, grain yield, crop residue, and total residual soil profile NO_3-N observed during the above periods were compared with corresponding GPFARM simulation outputs. Grain yield and crop residue dry mass data were pooled across all rotation phases and landscape positions at each location. Total soil profile water content and total soil profile residual NO_3-N data were

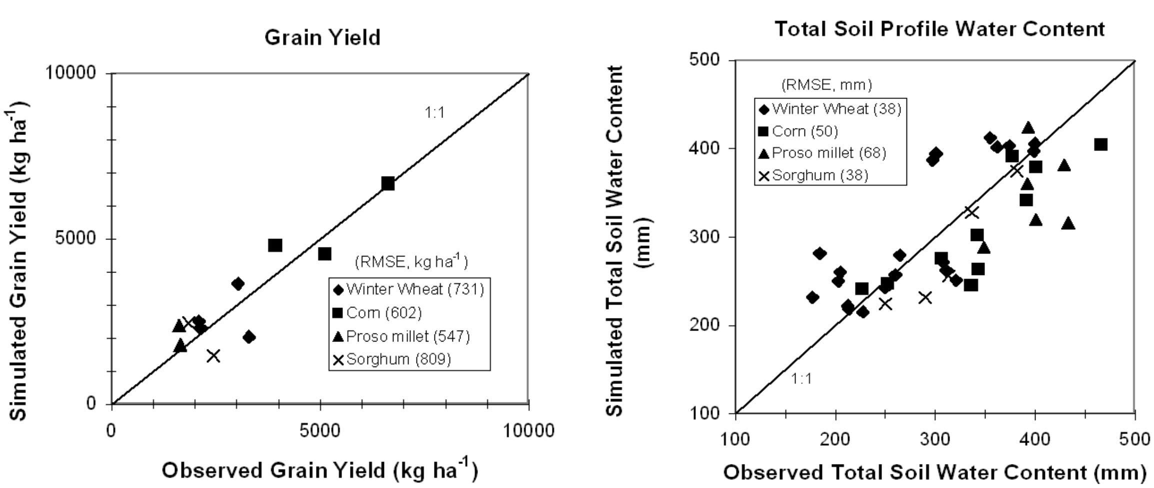

Figure 4. Simulated grain yield and total soil profile (150 cm deep) water content against observed values for calibration years at the Sterling experimental site toeslope position (adapted from Andales et al., 2003).

pooled across landscape positions at each location. The following three statistics were calculated to quantify the accuracy of the GPFARM simulations: relative error (RE), which shows bias of the predicted mean relative to the observed mean; root mean square error (RMSE), which shows the average deviation between predicted and observed values, regardless of sign; and index of agreement (d), which gives the proportion of the observed variance that is explained by the model. The simulated and observed coefficient of variation (CV), which shows whether or not simulated and observed variability are similar, was also calculated. Relative error was expressed in percent as:

$$\mathrm{RE} = \frac{\left(\overline{P} - \overline{O}\right)}{\overline{O}} 100 \qquad (1)$$

where $\overline{P}$ is the predicted mean and $\overline{O}$ is the observed mean. The RMSE was calculated by:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(P_i - O_i\right)^2}{n}} \qquad (2)$$

where P_i is the ith predicted value, O_i is the ith observed value, and n is the number of data pairs. The index of agreement was calculated as proposed by Willmott and Wicks (1980) and Willmott (1981):

$$d = 1 - \left[\frac{\sum_{i=1}^{n} \left(P_i - O_i\right)^2}{\sum_{i=1}^{n} \left(|P'_i| + |O'_i|\right)^2} \right], \quad 0 \le d \le 1 \qquad (3)$$

where P_i, O_i, and n are as previously defined, $P'_i = P_i - \overline{O}$, and $O'_i = O_i - \overline{O}$, where $\overline{O}$ is as previously defined, and the enclosing bars (| |) indicate absolute values. A d value of one indicates complete agreement between model predictions and observations. The RMSE and d values indicate the average event-by-event (short-term) prediction errors, as opposed to the RE, which is an arithmetic average over the duration of data (i.e., RE shows long-term bias). Additional statistical analysis was performed to determine differences among experimental sites with a one-way, fixed-effect ANOVA used to test the effect of location on measured data and GPFARM simulation model output responses. Tukey's least significant difference (LSD) was applied post-hoc to determine statistical significance between means with $P \leq 0.05$ considered significant. The ANOVA and Tukey's LSD analysis were conducted using SigmaStat 3.11 (Systat, 2006).

Finally, the evaluations of soil water and soil residual NO_3–N simulations in this study were limited to total soil profile amounts. In addition, observed grain yields affected by severe weed infestation, poor or erratic emergence due to hard surface soil conditions, hail damage, or killing frost were excluded from comparisons with simulated grain yields since the model was not designed to account for these extreme events. Steiner et al. (1987) and Cabelguenne et al. (1999) used similar approaches of data screening to limit evaluations to the validity domain of the models. GPFARM does include a weed module (Canner et al., 2002), but quantitative observations of infestation were insufficient for weed module calibration.

Results and Discussion

Grain Yield Evaluation

GPFARM was somewhat inconsistent in its ability to simulate measured grain yields. With the exception of corn yield, model performance was reasonable for long-term mean annual yields (both magnitudes and differences) between locations (table 4) but was less satisfactory for individual years. Only winter wheat and proso millet were grown at all three locations, with Walsh having significantly lower observed yields than Sterling and Stratton for both crops. Both corn and winter wheat had significantly higher observed yields at Stratton, whereas proso millet yield was significantly highest at Sterling. GPFARM simulations of winter wheat grain yield showed significantly lower yields at Walsh (matching the observed) but could not distinguish statistically ($P \leq 0.05$) between Sterling and Stratton (with simulated yield at Stratton being slightly less than Sterling, the opposite of the observed). Model simulations of proso millet yields could not statistically distinguish between the three locations, although the simulated yield at Walsh was lowest, matching the trend of observed yields being lowest at Walsh. In addition, GPFARM was able to correctly simulate corn grain yield differences between Sterling and Stratton.

The REs in simulated winter wheat grain yield were less than ±15%, with the lowest relative error occurring at Sterling (where winter wheat was calibrated at the toeslope position) and the largest relative error at Stratton (table 4 and fig. 5). Mean winter wheat grain yields were overestimated at Sterling and underestimated at Stratton and Walsh (fig. 5). Exhibiting the same trend as RE, RMSE values for winter wheat grain yield were lower at Sterling than at Stratton and Walsh (table 4).

The d values for winter wheat grain yield ranged from 0.46 at Stratton to 0.63 at Walsh. There was a tendency to underestimate wheat grain yield variability (CV) at Sterling and to slightly overestimate variability at Stratton and Walsh (table 4). The REs in simulated corn grain yield were the largest among the four crops (table 4 and fig. 5), with mean corn grain yields overpredicted by around 35% at Sterling and 33% at Stratton. Correspondingly, RMSE values for corn grain yield (table 4) were the highest (>2000 kg ha^{-1}) among the four crops, and were slightly lower at Stratton than at Sterling (where corn parameters were calibrated at the toeslope position). Agreement between simulated and observed corn grain yields was lower than that for winter wheat, with corn grain yield agreement ranging from 0.40 to 0.47 for Stratton and Sterling, respectively. The simulated CV was underestimated by approximately 10% at both locations (table 4). Two factors potentially contributed to overprediction of corn yield. First, the toeslope landscape position, which has more favorable soil and water conditions compared to the summit and sideslope landscape positions, was selected for calibration because potential HI should represent unstressed conditions with respect to water, temperature, or N (Williams et al., 1989). The corn HI value of 0.65 (obtained by calibration at the Sterling toeslope position) may have been too high, resulting in an overall bias towards overpredicting corn grain yield. Second, corn is very sensitive to water deficits and water stress during tasseling, silking, and early grain filling. Using long-term on-farm records (32 to 88 years) at five sites in northeastern Colorado, Nielsen (1996) showed a strong correlation between

Table 4. Evaluation statistics for simulated grain yield, total soil profile water content, crop residue, and total residual soil profile NO_3-N at the eastern Colorado experimental sites.

Location	No. of Observations	Observation Years	Observed Mean[a]	Observed CV	GPFARM Simulated Mean[a]	GPFARM Simulated CV	Relative Error	RMSE	*d*
Winter wheat grain yield									
			(kg ha^{-1})	(%)	(kg ha^{-1})	(%)	(%)	(kg ha^{-1})	(unitless)
Sterling	54	1989-1999	2316 b	27	2394 b	18	3.4	622	0.58
Stratton	72	1988-1996	2694 c	30	2294 b	31	−14.9	1082	0.46
Walsh	63	1989-1997	2009 a	30	1935 a	35	−3.7	701	0.63
Corn grain yield									
			(kg ha^{-1})	(%)	(kg ha^{-1})	(%)	(%)	(kg ha^{-1})	(unitless)
Sterling	40	1988-1999	3795 a	38	5134 a	28	35.3	2188	0.47
Stratton	30	1990-1996	4616 b	25	6131 b	16	32.8	2119	0.4
Proso millet grain yield									
			(kg ha^{-1})	(%)	(kg ha^{-1})	(%)	(%)	(kg ha^{-1})	(unitless)
Sterling	13	1988-1992	2049 b	29	1963	12	−4.2	706	0.13
Stratton	12	1988-1992	1915 b	25	2071	47	8.2	912	0.48
Walsh	6	1989-1990	1314 a	38	1602	21	21.9	495	0.67
Sorghum grain yield									
			(kg ha^{-1})	(%)	(kg ha^{-1})	(%)	(%)	(kg ha^{-1})	(unitless)
Walsh	58	1988-1997	2733	39	2621	39	−4.1	858	0.81
Total soil profile water content									
			(mm)	(%)	(mm)	(%)	(%)	(mm)	(unitless)
Sterling	783	1988-1999	276 a	25	299 a	22	8.3	61	0.79
Stratton	852	1988-1998	314 b	30	337 c	18	7.4	78	0.73
Walsh	658	1988-1998	303 b	16	322 b	17	6.3	54	0.71
Crop residue									
			(kg ha^{-1})	(%)	(kg ha^{-1})	(%)	(%)	(kg ha^{-1})	(unitless)
Sterling	224	1988-1999	3707 b	50	3568 b	41	−3.8	1530	0.76
Stratton	325	1987-1997	3371 b	64	3746 b	52	11.1	2099	0.7
Walsh	318	1988-1997	2237 a	72	2949 a	58	31.8	1912	0.62
Total soil profile residual NO_3-N									
			(kg ha^{-1})	(%)	(kg ha^{-1})	(%)	(%)	(kg ha^{-1})	(unitless)
Sterling	131	1988-1999	65 a	49	56 a	51	−14.6	32	0.69
Stratton	180	1987-1997	76 b	49	71 b	67	−6.6	50	0.59
Walsh	165	1987-1997	67 a	68	50 a	59	−25.1	52	0.45

[a] Within-column means followed by the same letter are not significantly different using Tukey's LSD at $P \leq 0.05$.

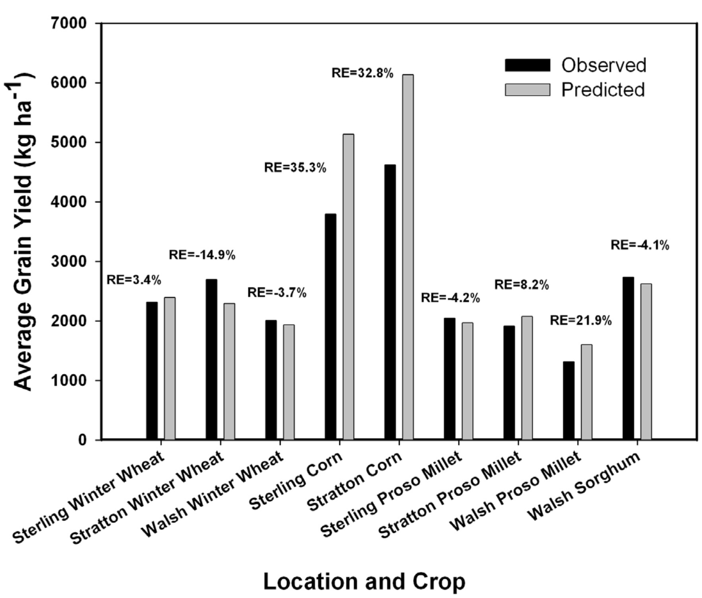

Figure 5. Simulated against observed winter wheat, corn, proso millet, and sorghum average dry mass grain yield values for the eastern Colorado experiment locations (RE is the relative error).

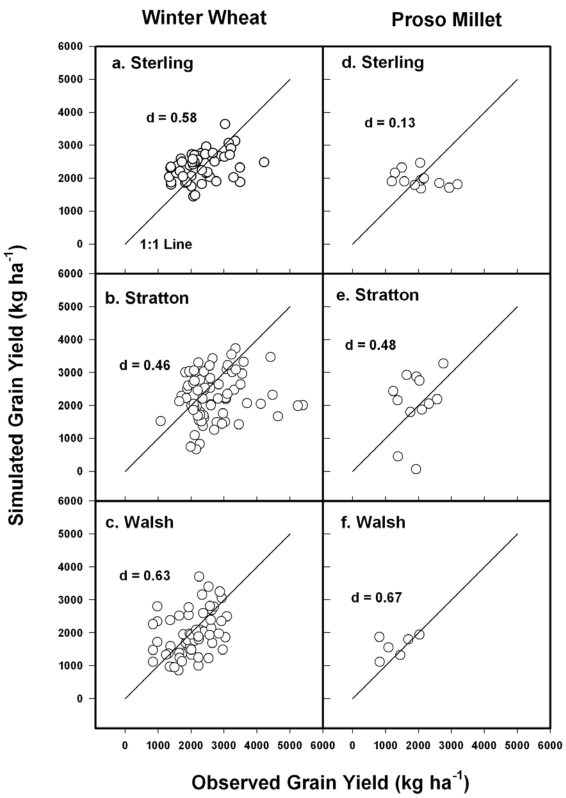

Figure 6. Simulated against observed winter wheat (a through c) and proso millet (d through f) average dry mass grain yield values for the eastern Colorado experiment locations (*d* is the index of agreement).

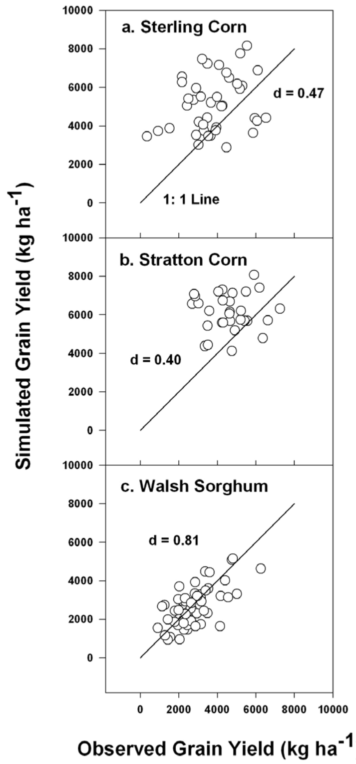

Figure 7. Simulated against observed corn (a and b) and sorghum (c) average dry mass grain yield values for the Sterling/Stratton (corn) and Walsh (sorghum) experiment locations (*d* is the index of agreement).

precipitation and corn grain yield during the six-week period of July 15 to August 25. The GPFARM crop growth model did not appear to sufficiently respond to soil water deficits during this six-week period, as evidenced by underadjustment of the simulated harvest-time HI values (data not shown). This was especially evident during years with substantially less than normal precipitation, e.g., 1989-1990 and 1994-1995 at Sterling (fig. 3).

Relative errors of proso millet grain yield simulations ranged from −4% at Sterling to 22% at Walsh (table 4 and fig. 5). The evaluation statistics at Walsh may not be very meaningful because there were only six observations. Because of consistently low yields, proso millet at Walsh was replaced by forage sorghum beginning in 1993. Similar to observations for winter wheat, the RMSE for proso millet grain yields was higher at Stratton than at Sterling (where millet was calibrated at the toeslope position) and Walsh (table 4). There was very low agreement between simulated and observed proso millet grain yields at Sterling (d = 0.13) with increasing improvement at Stratton and Walsh (d = 0.48 and 0.67, respectively). Overprediction in proso millet grain yield at Stratton and Walsh may again be due to the inability of the GPFARM crop growth model to sufficiently respond to soil water deficits during critical growth periods. The simulated proso millet CV was underestimated at Sterling and Walsh and overestimated at Stratton; the differences in observed and simulated proso millet grain yield CVs were the largest among the four crops (table 4). This may be due to the low number of observations at the three experimental locations, which contributed to high variances in both the observed data and simulated model output response. For sorghum, which was planted only at Walsh, the RE was very low at −4% (table 4 and fig. 5). The RMSE value (858 kg ha^{-1}) was in the middle of the range of winter wheat and proso millet RMSE values (500-1100 kg ha^{-1}), and the index of agreement value was the highest among the four crops at 0.81. The simulated CV of sorghum grain yield was nearly identical to the observed CV.

Overall for the four crops, table 4 and figure 5 show that the lowest RE value was obtained with winter wheat at Sterling (RE = 3.4%), and the best combination of RE and index of agreement value was obtained with sorghum at Walsh (−4.1% and 0.81, respectively). Long-term trends in overprediction and underprediction also are manifested in the RE statistics presented in table 4 and figure 5. Based on the RMSE values, the best simulations of grain yield were for proso millet at Walsh (495 kg ha^{-1}) and the worst were for corn at Stratton (2188 kg ha^{-1}). However, RMSE is difficult to compare across crops because it depends on the absolute magnitude of the variable, e.g., observed corn grain yield is much higher than observed winter wheat grain yield, so corn should have higher RMSE values.

Similar to RE, high RMSE values typically indicate either strong overprediction/underprediction or considerable scatter when measured data are plotted against simulated model output response. This is evident in figure 6, where winter wheat grain yield was mostly underpredicted at Stratton (fig. 6b) and proso millet was overpredicted at Walsh (fig. 6f). It is also evident in figure 7, where corn grain yield was mostly overpredicted at Sterling and Stratton (figs. 7a and 7b, respectively). Index of agreement values ranged from a low of 0.13 for proso millet grain yield at Sterling to a high of 0.81 for sorghum grain yield at Walsh. Simulated

CV was within ±10% of observed among all four crops, with the exception of the simulated proso millet grain yield CVs at all three experimental locations.

Based on the above evaluation, the EPIC-based crop growth model in GPFARM seems most appropriate for estimating long-term average crop yields or trends in yields rather than simulating year-to-year variability in crop yields in eastern Colorado. Other researchers who have evaluated the EPIC crop growth model or its implementation in GPFARM have reported similar results (e.g., Kiniry et al., 1995; Jara and Stockle, 1999; Cabelguenne et al., 1999; Andales et al., 2003).

In this article, only simulated grain yield results are presented; however, Andales et al. (2003) also analyzed simulated biomass and HI results. They found that for corn, biomass was overpredicted by 35% to 45%, whereas mean simulated HIs were similar to observed values. For winter wheat, biomass was reasonably predicted, but the agreement between mean simulated and observed HIs was poor. Andales et al. (2003) concluded that errors in prediction of biomass seem to be the major reason for errors in simulated grain yield for corn, whereas in winter wheat, the contribution of HI to error in simulated grain yields was the dominant factor. Cabelguenne et al. (1999) also confirmed that EPIC overestimated vegetative biomass and grain production, especially under conditions of pronounced water stress.

Soil Water Content, Crop Residue, and Soil Residual NO_3-N Evaluation

GPFARM better simulated trends between locations (both magnitudes and differences) in total soil water content and crop residue than it did for grain yield predictions (with the exception of sorghum grain yield). Similarly, GPFARM correctly distinguished differences in total soil residual NO_3-N between locations but moderately underestimated mean values at all three locations. For total soil profile water content and residual NO_3-N, Stratton had the highest values for both observed and simulated totals (table 4). Sterling had the highest amount of crop residue based on observed data, but GPFARM simulations showed Stratton with the highest amount of crop residue. In simulating differences between locations, GPFARM was able to correctly distinguish statistically significant differences ($P \leq 0.05$) between all locations for both crop residue and total soil profile residual NO_3-N. For total soil profile water content, observed data showed statistically significant differences between Sterling and the other locations, but no difference between Stratton and Walsh (table 4). In comparison, GPFARM predicted statistically significant differences between all locations for total soil profile water content (table 4).

Overall, total soil profile water content simulations were better at Sterling (intermediate RMSE and highest *d* value) than at Stratton and Walsh, although Walsh had the lowest soil profile water content RE at 6%. This may be attributed to better assessment of soil properties and more complete

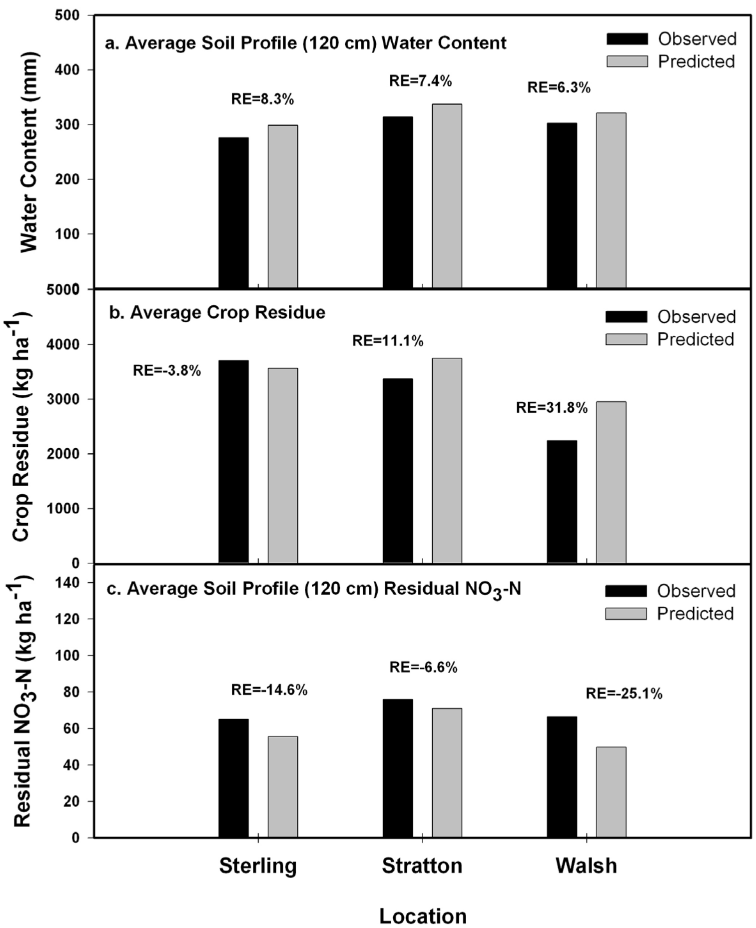

Figure 8. Simulated against observed (a) total soil profile (120 cm) water content, (b) crop residue, and (c) total soil profile (120 cm) residual NO_3-N values for the eastern Colorado experiment locations (RE is the relative error).

precipitation records at Walsh (several on-site precipitation records were missing at Sterling and Stratton, especially during winter months). These precipitation records were filled using data from the nearest weather stations (within 30 km of the experimental sites) in the Colorado Climate Center (Colorado State University) network. Mean water content was overpredicted for all three locations, but relative errors in mean water contents were all less than 10% (table 4 and fig. 8). The reasons for the overprediction were difficult to identify because of lack of experimental information on some water balance components (e.g., surface runoff) and on root distribution in the soil profile. However, GPFARM simulated the correct timing for most observed drying and wetting events over time for all three locations (data not shown). Simulated and observed variability in soil water content were very similar at Sterling and Walsh; simulated variability was less than observed at Stratton (table 4).

GPFARM simulations of total soil water content in the profile were comparable in accuracy to those of RZWQM, which simulates the soil water balance with greater process detail.The index of agreement values between GPFARM and observed total soil profile water content ranged from 0.71 at Walsh to 0.79 at Sterling (table 4). In comparison, Wu et al. (1999) reported lower *d* values (0.54 to 0.59) for total water content simulations of RZWQM during two seasons in a sandy soil near Princeton, Minnesota. The errors in soil water content simulations were possibly well within the range of spatial variability considering that only two point measurements were taken per treatment (1500 m^2 average plot area per treatment). GPFARM assumes a 2 h duration for all storms, and the ability to use actual storm intensities from breakpoint rainfall data would almost certainly improve simulation of soil water content. Furthermore, GPFARM does not simulate rainfall interception by crop residue, but the addition of this process would potentially improve the soil water content simulations.

The crop residue RE values were lower at Sterling and Stratton (RE = −4% and 11%, respectively) than at Walsh (RE = 32%; table 4). The RMSE values were lowest at Sterling and similar in magnitude to the corn grain yield RMSE values (~2000 kg ha^{-1}; table 4). In addition, better agreement between simulated and observed crop residue was obtained at Sterling and Stratton (*d* = 0.76 and 0.70) than at Walsh (*d* = 0.62). The simulated CV was underestimated at all locations, with the simulated CV being closer to the observed CV at Sterling than at Stratton or Walsh (table 4). Amounts of surface crop residue are closely tied to amounts of crop biomass produced. The model assumes that 80% of aboveground biomass is added to existing surface crop residue at harvest. Thus, errors in biomass prediction translate into errors in crop residue prediction. Inaccuracies in the simulation of residue addition during harvesting and subsequent decay may have also contributed to errors (Andales et al., 2003). Finally, all cropping systems were under no-till management in this study, with moderate amounts of crop residue on the soil surface. Mohamoud and Ewing (1990) and Savabi and Stott (1994) showed that interception of precipitation by crop residue can significantly reduce infiltration, especially during low-intensity rainfall events occurring over dry crop residues.

The soil residual NO_3–N relative error was lowest in absolute magnitude at Stratton (RE = −7%), followed by Sterling and Walsh (RE = −15% and −25%, respectively).

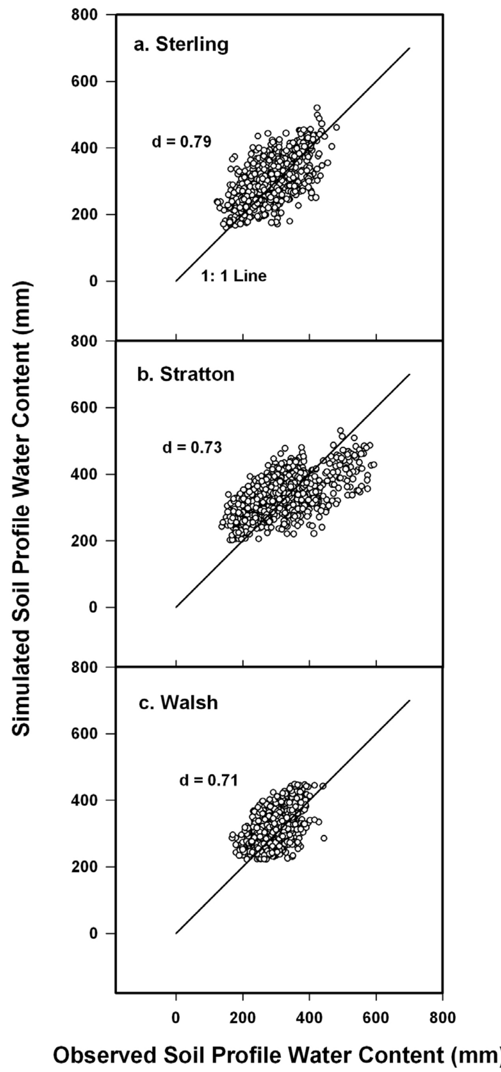

Figure 9. Simulated against observed total sol profile (120 cm) water content values for the (a) Sterling, (b) Stratton, and (c) Walsh experiment locations (*d* is the index of agreement).

Simulated means were consistently underestimated at all three locations (fig. 8), and the RMSE values were lowest at Sterling and greatest at Walsh. Table 4 shows that the highest *d* value was obtained at Sterling (*d* = 0.69), while *d* values were much lower at Stratton and Walsh (*d* = 0.59 and 0.45, respectively). In general, predicted soil residual NO_3–N variability was close to observed, with the exception of a larger (~18%) overprediction in variability at Stratton (table 4). Predicted soil residual NO_3–N was highly sensitive (positively correlated) to the amount of organic matter (table 2) in the soil and negatively correlated to crop leaf area index (table 3). Numerous interrelated plant-soil-environment factors that influence nitrogen cycling in the soil make prediction of residual soil profile NO_3–N a difficult task. Predicting NO_3–N amounts over an extended number of years is an even greater challenge, e.g., a lack of within-season residual NO_3–N data prevented year-to-year evaluation of NO_3–N root uptake. Overall, the simulations of total soil residual NO_3–N seem reasonable, especially with respect to lower RMSE values, but further improvements in GPFARM modeling of crop NO_3–N uptake and N dynamics may be needed.

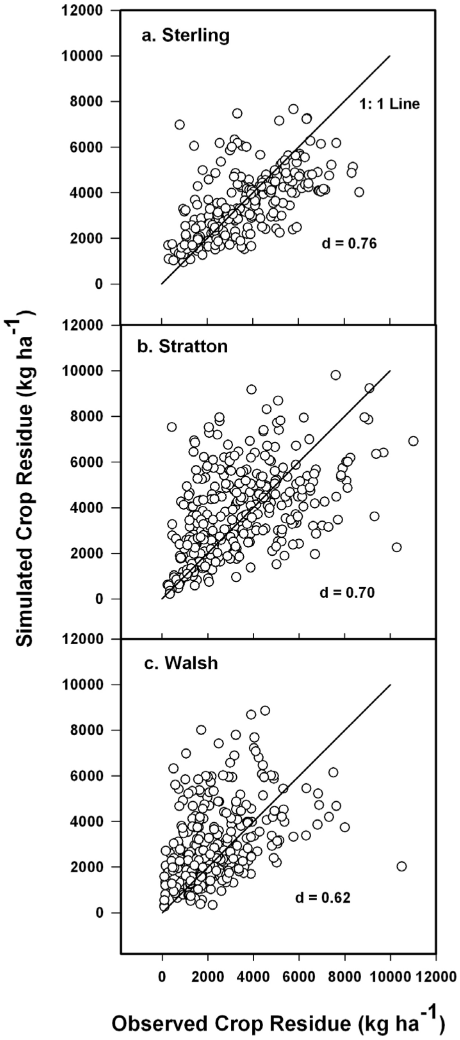

Figure 10. Simulated against observed total crop residue values for the (a) Sterling, (b) Stratton, and (c) Walsh experiment locations (*d* is the index of agreement).

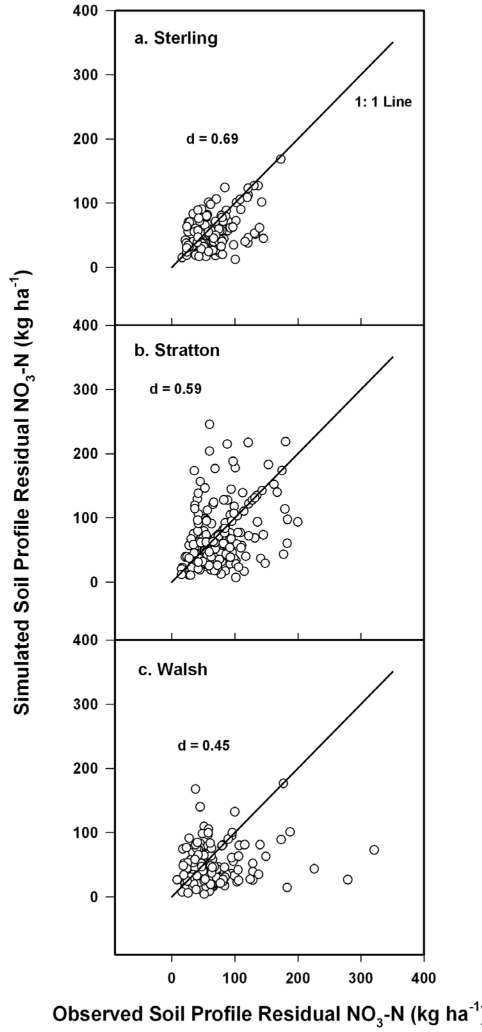

Figure 11. Simulated against observed total soil profile (120 cm) residual NO_3-N values for the (a) Sterling, (b) Stratton, and (c) Walsh experiment locations (*d* is the index of agreement).

A comparison of RE values for total soil profile water content, crop residue, and total soil residual NO_3-N reveals that GPFARM's long-term predictions were generally within a range of ±20% or better (table 4 and fig. 8). Overall for the three process state variables, the lowest RE value was obtained with crop residue at Sterling (–3.8%). The highest RE values were found for crop residue and total soil residual NO_3-N at Walsh (31.8% and –25.1%, respectively). Not surprisingly, the observed CVs for these variables were very high at Walsh (~70%; table 4). Although RMSE values are unit dependent (and cannot be directly compared across the three process state variables), total soil profile water content had fairly low RMSE and high index of agreement (*d*) values, as illustrated by the low scatter and lack of prediction bias in observed against simulated values in figure 9. Figure 10 shows that, compared to total soil profile water content, crop residue prediction exhibited slightly lower index of agreement values (caused by both overprediction and larger scatter). Total soil residual NO_3-N was somewhat underpredicted (fig. 11), especially at Stratton and Walsh, even though the RMSE values were fairly low. Overall, index of agreement values ranged from a low of 0.45 for total soil residual NO_3-N at Walsh to a high of 0.79 for total soil profile water content at Sterling (table 4). Table 4 also shows that simulated CV was within ±20% of observed CV for all three process state variables; differences in simulated CVs were the largest for crop residue and total soil residual NO_3-N (which also had the highest observed CVs).

Summary and Conclusions

Compared to other more complex agricultural system models, and considering the intended purpose of GPFARM (i.e., to serve as a whole-farm/ranch DSS for long-tem strategic planning across the Great Plains), the model appears to have reasonably simulated average dry mass grain yield (with the exception of corn), total soil profile water content, dry mass crop residue, and total residual soil profile NO_3-N pooled across landscape positions at the eastern Colorado experimental sites. Overpredictions in corn yield were a result of too high a value for the corn HI crop growth parameter and to the inability of the GPFARM crop growth model to correctly respond to soil water deficits at critical growth periods. GPFARM model performance was reasonable for long-term mean annual winter wheat, proso millet, and sorghum grain yield predictions, but was less satisfactory for winter wheat and proso millet on an annual basis (fig. 6). GPFARM simulations of total soil water content in the profile were quite reasonable; in fact, they were similar in accuracy to those produced by the RZWQM, which simulates soil water balance with greater process detail. Dry mass crop residue predictions were also very reasonable for Sterling and Stratton, but not as robust at Walsh. Simulated mean values of total residual soil profile NO_3–N were moderately underestimated at all three locations.

GPFARM correctly simulated long-term location differences in corn grain yield, crop residue, and total soil profile residual NO_3–N. Results were mixed on simulated statistical differences in winter wheat grain yield, proso millet grain yield, and total soil profile water content. However, the model correctly predicted that the Sterling and Stratton experimental sites were generally more productive in grain yield than the Walsh site. In general, GPFARM had more trouble simulating location differences for grain yield than for total soil profile water content, crop residue, and total soil profile NO_3–N. The unavailability of within-season crop growth data made evaluation of the crop growth model difficult, and calibration was based only on final grain yield and biomass data. In addition, the soil profile water content measurements were too sporadic to aid in pinpointing problems with GPFARM grain yield prediction. Overall, however, GPFARM performed reasonably well in simulating long-term statistical differences among the eastern Colorado dryland locations along a gradient of ET demand.

GPFARM simulations for average dry mass grain yield, total soil profile water content, dry mass crop residue, and total residual soil profile NO_3–N illustrate the difficulty in assessing model performance when using different statistical evaluation methods. It is important to remember that RE is an arithmetic average over the duration of data, i.e., the RE shows that long-term bias in the simulated against observed deviations can cancel out (especially if the model both overpredicts and underpredicts with similar frequency). The RMSE and d values, however, indicate the average event-by-event (short-term) prediction errors and should be considered more robust indicators of model performance, e.g., the index of agreement accounts for individual simulated against observed deviations. Overall analysis of simulation results using the discrete evaluation statistics shows GPFARM to be less efficacious for short-term predictive ability.

In this research study, the importance of reproducing long-term trends between experimental locations was emphasized. However, careful examination of the short-term simulation results raises the following question: How important and reliable is a long-term trend analysis if the seasonal or annual model predictions are less accurate? The answer depends on the intended purpose and use of the model. GPFARM appears to be adequate for strategic planning of cropping systems across multiple dryland locations, but the simulation model may be lacking in accuracy for predictions on a short-term (tactical) planning basis (especially for grain yield). For example, more rigorous testing and improvement of the EPIC-based crop growth model in GPFARM is needed under dryland conditions in eastern Colorado using detailed observations of soil water content at depth, biomass, LAI, phenology, harvest index and grain yield for various crops. Additional testing and improvement of the C and N cycling component is needed as well. It is anticipated that improvements in the crop growth and environmental components (including improved parameterization) of the GPFARM simulation model will improve its accuracy for both strategic and tactical applications.

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